Prospects of Integrating BIM and NLP for Automatic Construction Schedule Management

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Abstract –

In construction, project schedules are still created and updated manually, which takes time, causes errors, and leads to poor planning and scheduling, one of the main reasons for project delays today. Consequently, overcoming these challenges requires an automated schedule management method that extracts information and knowledge from existing and previous databases to improve construction planning and scheduling. Natural Language Processing (NLP) and Building Information Modeling (BIM) are two technologies that can revolutionize construction planning and scheduling by providing the ability to extract and interpret data from project documents, models, and past project knowledge bases. This paper reviews the state-of-the-art to understand the current research and methods that use NLP and BIM to automate construction schedule management (CSM). This in-depth study examines the knowledge potential of both technologies and integration possibilities in the construction planning and scheduling context. It also highlights the popular methods in recent times, a generalized workflow of NLP-based data processing, and limitations of existing approaches in practical applications. Finally, this study introduces three future research directions for integrating BIM and NLP for automated CSM.

Keywords –

Natural Language Processing; Building Information Modeling; Construction Planning and Scheduling; Data Extraction; Data Integration; Information Retrieval; Optimization; ChatGPT.

1 Introduction

Construction Schedule Management (CSM), a vital process in the Architecture, Engineering, and Construction (AEC) industry, includes planning, coordinating, and controlling tasks to complete a project within the prescribed time, cost, and quality. However, the inability to manage construction schedules significantly contributes to delays and cost overruns. Research has shown that deficiencies in planning and scheduling are the primary causes of cost performance issues among contractors, consultants, and clients [1]. Furthermore, poor planning and scheduling conflicts are among the top reasons for project delays [2][3]. Current approaches toward CSM typically rely on manual procedures (creating and updating schedules), which can be time-consuming and susceptible to human errors [4]. Although software solutions are available, they often require labor-intensive manual input [5]. Delays and cost overruns resulted from poor planning and scheduling, and reliance on manual procedures necessitate automation in CSM. Automation provides benefits such as efficient and precise scheduling, reduced human errors, enhanced update speed and accuracy, and real-time data visualization. Additionally, automating the CSM process can eliminate the labor-intensive manual input required by current software solutions, thereby elevating the overall efficiency and performance of the process.

Researchers have employed several methods in the past three decades to automate the scheduling process in construction projects, such as case-based reasoning, knowledge-based systems, model-based approaches, meta-heuristic algorithms, expert systems, and learning-based methods [6]. However, their widespread adoption is hindered by several reasons. A few of those reasons are: each method follows manually formed and maintained work templates, reducing the chance of generalizability across different projects; lack of flexibility in how construction knowledge is stored in existing construction method model templates; a limited ability to automate the learning of construction knowledge from existing records; lack of validation of the applicability of existing automated planning systems on real-life construction projects; and the decoupled nature of research on automated planning and schedule optimization [7].

In recent years, BIM and NLP have been two emerging information technologies in the Architecture, Engineering, and Construction (AEC) industry [8]. These technologies have significantly impacted project management by improving communication, collaboration, and efficiency of information flow. BIM, which revolutionized the AEC industry, provides a digital representation of a building's physical and functional characteristics. Building Information Modeling (BIM) can automatically generate and optimize schedules using data embedded in the model, reducing reliance on project planners' knowledge and experience and resulting in more efficient and accurate schedules. BIM data, including spatial, geometric, quantity, relationship, and materials, can be leveraged to automate the generation of construction schedules [5].

Natural Language Processing (NLP) is a sub-field of artificial intelligence (AI) that analyses how computers interact with human language. NLP is divided into three parts: syntactic, semantic, and ontological. Syntactic deals with language structure, semantic deals with the meaning of language, and ontology deals with the representation of knowledge in the language [9]. NLP techniques can speed up information extraction from construction documents and enable automatic interpretation of construction processes and interdependence logic across building activities. Applications of NLP can be seen in many areas of the AEC industry. For example, Shen et al. [8] used NLP to extract, process, and analyze data from BIM models to deliver real-time information for safety compliance. Jafari et al. [10] developed an automated NLP and machine learning (ML) tool to analyze contract documents. Other NLP applications include design and code compliance checking [11] and facility maintenance [12].

The power of NLP can also be leveraged to automate the CSM process. It can automatically learn company-specific construction knowledge from past project schedules, generate new schedules, validate the logic of existing schedules [13], and check the completeness and accuracy of the schedules [9].

Recognizing the potential of BIM and NLP individually for automated CSM, this study explores the integration prospects of BIM and NLP in Automated CSM. For this purpose, it reviews relevant academic papers on automated construction management and highlights the state-of-the-art techniques, their methodologies and generalized data processing workflows, and challenges. Finally, it underlines three possible future research directions to improve the BIM and NLP integration for automated CSM. The paper contributes to identifying data sources and types from which information and knowledge for automated construction schedule management (CSM) can be extracted through NLP.

Section 2 of this paper provides an overview of the automated CSM, Section 3 proposes future research directions, and Section 4 summarizes and concludes the study.

2 Overview of Construction Schedule Management

According to the project management institute (PMI), CSM includes schedule preparation, analysis and optimization, schedule update, and schedule control. The current industry practice for schedule management is as follows. First, the work breakdown structures (WBS) and activities are defined from the project scope documents. Next, expert construction professionals use their experience and expertise to identify activity sequences and resource requirements. Considering the common resource efficiency factors, schedulers calculate activity durations using a three-point estimation method: program evaluation and review technique (PERT) [1] or parametric estimation. Commercial project management software tools (e.g., MS Project and Primavera P6) are used to conduct critical path analysis [14], resource leveling, and time-cost trade-offs to analyze and optimize the baseline schedules. During project execution, schedulers manually update construction programs with progress and resource information from the daily progress reports. Projects with the last planner system [15] necessitate alignment of master schedules and weekly lookahead schedules for an accurate schedule update. Empirical delay analysis: time impact analysis (TIA), window analysis (WA), risk analysis, and recovery schedule preparation are conventional ways of schedule controls in the construction industry. The traditional CSM demands a considerable amount of manual effort and expert judgment. Young schedulers with less experience in the construction industry often face difficulties in producing a good quality schedule. Consequently, the project faces contractual challenges, stakeholder dissatisfaction, and disputes.

Researchers have constantly looked for opportunities to automate the CSM process to overcome these challenges. In recent times, advanced deep learning-based data analytic techniques [16] have created a new opportunity to use NLP techniques to extract the tacit knowledge from past schedules for new schedule development. Simultaneous integration of BIM, computer vision, and NLP has eased the process of schedule updates [17]. ML-based delay and risk prediction models have improved the effectiveness of schedule control methods.

Table 1 highlights the conventional and state-of-the-art techniques in each stage of schedule management. The following sub-sections discuss the state-of-the-art methods, their methodologies, and their limitations.

Table 1: Conventional practices and state-of-the-art techniques for CSM

Schedule management	Conventional practices	State-of-the-art

Schedule preparation		
Defining WBS and activities	I	A, B
Defining logic	I	A, B, C, D
Defining resources: Type and work	I	-
Defining durations	II, III, IV	J
Schedule Quality control	VIII	B
Schedule analysis and optimization		
Critical path analysis	V	-
Risk path analysis	V	I
Resource leveling	V	-
Time-cost tradeoff	I	E
Schedule update		
Progress update	VI	F
Resource update	VI	-
Logic update	I	-
Linking long-term and short-term schedules	I	H
Schedule control		
Delay analysis and prediction/ EVM	V, VII	I, G
Schedule recovery	I	-

(A) References of state-of-the-art techniques

Ref. Code	State-of-the-art	Reference Paper
A	Graph-Based Automated Construction Scheduling	[18]
B	NLP-based learnings from past project schedules	[9], [19], [20], [13], [21], [22]
C	Activity and sequencing from the BIM database and schedule ontology	[23]
D	IFC-based 4D	[24]
E	Schedule optimization/ Time-Cost tradeoff through GA	[18], [25]
F	Automatic progress updates from reality models	[17]
G	Digital Twin information system	[26]
H	Aligning master schedule and weekly plans	[27]
I	ML-based schedule risk analysis	[28]
J	NLP-based cost and time prediction	[10]

(B) References of conventional practices

Ref. Code	Standard procedures followed in the construction industry
I	Expert judgment
II	Resource Efficiency Factor
III	PERT
IV	Parametric estimation
V	PM Software
VI	Manually from DPR
VII	TIA/ WA
VIII	DCMA Schedule assessment

2.1 State-of-the-art techniques in automatic schedule management

2.1.1 Model-based automated scheduling

As schedule preparation is highly manual and time-consuming, researchers have tried several methods to automate it in the past few years. Early studies in this direction tried to generate schedules automatically leveraging IFC schemas of BIM [24]. Sigalov & König [29] tried BIM-based construction schedule generation using graph-based and feature-based indexing techniques. Faghihi et al. [30] utilized BIM data and genetic algorithms to generate and optimize construction schedules based on time, cost, and job-site movements. Using BIM attributes of structural elements to develop a list of work packages, estimate their duration, and generate schedules utilizing a combination of rule-based and case-based reasoning was tried by Wang & Rezazadeh Azar [31]. Later, Wu et al. [23] tried querying the BIM database through NLP for BIM object retrieval. One could use BIM object hierarchy to formulate construction sequencing knowledge [14]. Schedule generation from BIM using VBA, Excel, and trade-off analysis through Genetic Algorithm (GA) was investigated by ElMenshawy & Marzouk [25]. Singh et al. [32] introduced an AI framework for automatic scheduling and optimization of pipe system installation using BIM, ML, and heuristic techniques, integrating data and site knowledge. Combined with various optimization algorithms, an automated and optimized 4D BIM approach was proposed by Fazeli [33] for estimating construction time by leveraging resource specifications and geometric information from BIM. Although BIM-based techniques are helpful for automatic schedule preparation, BIM models with low Levels of Development (LOD) are often unsuitable for construction planning and monitoring [34]. Also, design approval, permit application, and procurement-related activities cannot be directly retrieved from BIM information.

2.1.2 Learning-based automated scheduling

Recently, for automated schedule preparation and schedule quality control, researchers have focused on NLP-based construction knowledge extraction from past project schedules [9][13]. Amer and Golparvar-Fard [20] proposed a dynamic process template for modeling construction works' planning and sequencing by learning from past project schedules. Later, Amer et al. [19] leveraged deep-learning-based NLP to predict and critique construction sequences of activity pairs. A recent study by Hong et al. [18] used a Graph Convolutional Network (GCN) to learn and identify activity types and sequences from input features, such as relative activity duration and position, text descriptions of activities and

WBS, logic links, and lags between activities. So far, significant research efforts have gone into learning activity definitions and construction sequences from past projects. Future research on automated schedule preparation may look into the prospects of the resource type and quantity identification and activity duration predictions from the knowledge of past projects.

Optimization of automatically generated schedules is essential to ensure better schedule quality. Hong et al. [28] used Genetic Algorithm (GA) to optimize the resource allocation and duration to generate a time- and cost-efficient schedule. Other meta-heuristic approaches, such as Ant Colony Optimization (ACO) and Particle Swarn Optimization (PSO), could be tried.

Schedule update is another step of CSM where the latest technologies bring significant automation. For updating a project master schedule with the information retrieved from weekly lookahead plans, an automatic schedule alignment method proposed by Amer et al. [27] reduced significant manual efforts. Automatic progress information extraction from reality models (as-built point clouds) and alignment with project schedules through NLP-based information extraction and matching can significantly automate the schedule update process [17]. The digital twin information system integrates 3D models and other digital information for project control. It applies AI tools to compare construction projects' as-planned and as-built status in real-time and predict the future state of the project [26].

ML-based schedule risk analysis and delay prediction methods [28] are a significant development in effective construction schedule control. Project managers can proactively mitigate such risks or delays to maintain the project timeline and budget.

2.2 Details of learning-based methods

Model-based methods generally rely on structured data (e.g., IFC and UML), and construction schedules prepared by human engineers are usually less structured. Learning-based methods can handle unstructured data to extract required knowledge from human language texts. As learning-based methods outperformed model-based methods in the generalizability of applications, this section only discusses the methods related to learning-based techniques.

Currently, three popular deep-learning models that support the learning-based CSM methods are Long Short Term Memory Recurrent Neural Network (LSTM-RNN) [19], the Transformer machine learning model [27], and Graph Convolutional Neural Network (GCN) [18].

Amer et al. [13] attempted to automate construction planning and scheduling by proposing a novel method to learn construction planning. This study introduced a generative model called Dynamic Process Templets (DPT), built upon LSTM-RNN. Testing 78,704 activities from a historical data set confirmed the learning capability of the model with 76% to 98% accuracy. Amer et al. [13][19] also used LSTM architecture-based model to validate logic and ensure schedule quality. Amer et al. [27] used a transformer machine learning model to learn the dependencies between long-term and short-term plans based on schedule activity and lookahead planning task descriptions. The knowledge learned by the model was used to generate a list of lookahead planning tasks based on an input master schedule activity. A Graph Convolutional Network (GCN) was used by Hong et al. [18] to learn and identify activity types and sequences from input numerical, textural, and graphical features, such as relative activity duration and position, text descriptions of activities and WBS, logic links, and lags between activities.

2.3 Generalized workflow of learning-based methods for CSM

Figure 1 shows a generalized workflow for automated CSM through NLP-based data processing. Creating a construction schedule with NLP involves several steps, starting with the significant part of data acquisition, where all relevant information is collected from BIM and construction documents.

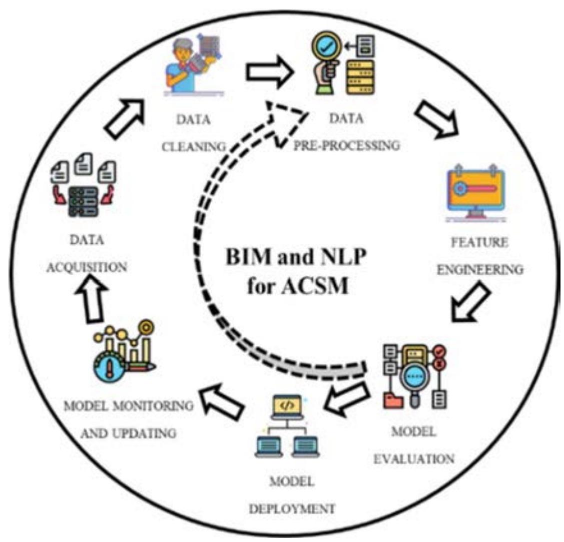

Figure 1. A generalized workflow for NLP-based data processing

The first step is data cleaning, which includes removing duplicated or irrelevant data and correcting errors to ensure data consistency. After cleaning, data pre-processing is performed. This step uses NLP techniques, such as tokenization, lowercasing, stop word removal, POS tagging, stemming, lemmatization, and named entity recognition, for extracting relevant information from the raw data. However, the data cleaning and pre-processing depend on the input data source and the output data requirement. The output data may need certain information to be extracted, structured, and presented in a specific way, depending on the quality, consistency, format, and level of detail of the input data. The pre-processed data are then transformed into features that are used to train a learning-based schedule-generation model. Also, it is critical to select and alter the data precisely to ensure the features are relevant, high-quality, and representative and reduce the amount of linked and duplicated characteristics. The model is evaluated and refined using co-reference resolution, information modeling, knowledge matching, and text classification techniques. Furthermore, the data evaluation results can help improve the data pre-processing step by identifying issues with the data and providing insight into how to address them. The model can be enhanced by using the evaluation results to improve the data pre-processing step, which ensures high quality of data and captures the relevant features.

Once the model is finalized, it is deployed to manage the construction schedule, which is automated to reduce the time and effort required by management personnel. By ensuring that the data are accurate and up-to-date, data monitoring and updating can assist in improving the data acquisition process and further training the construction schedule generation model for obtaining a more realistic timetable. This procedure can change the model to reflect changes in the real world, and its performance can be enhanced over time.

2.4 Challenges and limitations of learning-based methods

Researchers have identified a few challenges and limitations of using learning-based schedule preparation and management methods. For example, the proposed models learn with an assumption of the same type of precedence dependencies [20]. Considering information regarding productivity and risk factors in the model is still a challenge [20]. Due to different project sizes, activity duration and resource usage cannot be adapted straight away from previous projects [18]. Although the model presented by Amer et al. [19] attempts to validate the logical dependencies, it does not provide an overall assessment of the quality of the schedule; Minimizing biases and irregularities and unpredictability of the impact of the mistakes remains a limitation for the data-driven models [27]. The learning-based models are company-specific [13] and work well mainly for data collected from the same companies.

Overall, achieving high accuracy and moving towards complete automation remained a significant challenge in an attempt to automate CSM. Alternatively, a human-assisted approach could be adopted to support the current automated schedule generation [27].

3 Future research directions

In practice, CSM utilizes information from various construction documents and building models. However, the automated CSM methods have either used information retrieved from BIM or past schedules. There is also limited integration of BIM and NLP observed in past automated CSM literature. This section proposes three research areas where future researchers can focus on improving the state-of-the-art.

3.1 Integration of BIM and NLP in Automated CSM

Integrating BIM and NLP within CSM can prove beneficial in addressing barriers to the widespread adoption of automated planning and scheduling methods. BIM can provide a centralized repository for storing construction knowledge, allowing for greater flexibility in scheduling algorithms. NLP can automate the learning of construction knowledge from existing records, reducing the dependency on manual work templates. Additionally, the integration of BIM and NLP can aid in the automatic generation of dynamic work templates and facilitate their inclusion in integrated planning, scheduling, and optimization systems, allowing for more efficient and accurate management of projects. Furthermore, with the adoption of the BIM methodology, which is centered on producing and exchanging digital models and artifacts [35], the AECO sector is moving towards a model-based approach. Despite this shift, the industry continues to rely heavily on document creation and exchange. NLP can be used to overcome this. By automating extracting and exchanging information from digital models and artifacts, NLP can revolutionize how information is handled in the AEC industry, improving efficiency and accuracy in Automated CSM.

3.2 Data-to-information flow for BIM and NLP-based automated CSM

This section highlights different data sources and types that can contribute to the information requirements for CSM. BIM provides spatial data (location and position of the elements), geometric data (shape and size of the elements), and identification data (element IDs, e.g., GUIDs) [11]. Standards, specifications, and company-specific resource productivity rates are collected for resource (manpower, materials, machinery) requirement calculation, cost estimation, and budget preparation for the project. Besides, the contract documents provide the details of the scope of work, milestones, and other specifications needed to create a realistic construction schedule agreed upon by all stakeholders [10]. Previous project schedules and reports from past projects are used for learning activity descriptions, logical sequences, and dependencies required for automatic schedule development [8, 29]. Figure 2 shows a mapping between the data collected from construction documents and models and the information requirements for CSM. Based on the construction scheduling experience and literature review, the authors created a data-to-information flow map that connects data types and sources with information requirements for CSM. The mapping is shown in Figure 2. Future research may develop specific methods for multi-source data integration and information and knowledge retrieval for automated CSM.

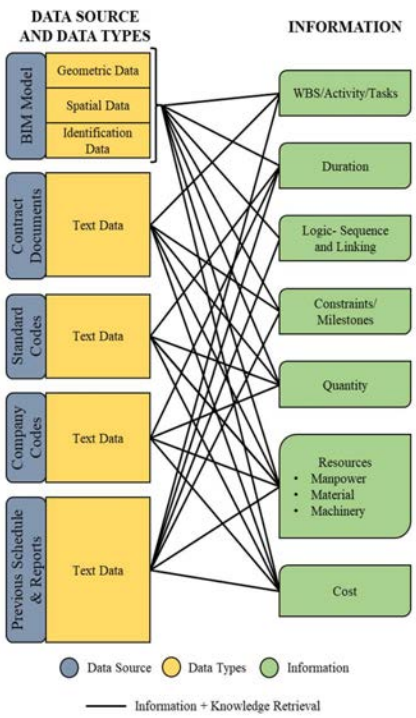

Figure 2. From data to information and knowledge retrieval for automated CSM

3.3 Schedule generation by Large Language Models (LLM): ChatGPT

ChatGPT is a large language model developed by OpenAI based on the GPT-3.5 architecture. It can generate human-like text and has been trained on a massive dataset of internet text, allowing it to create high-quality responses to a wide range of prompts [36]. Using ChatGPT for construction schedule generation can provide a quick and easy way to generate general schedule information for a construction project [37]. It can be beneficial for planning and budgeting, as it can create a schedule quickly and provide a starting point for further refinement and adjustment. This method is not limited to specific project types, as it includes general information that can be adjusted according to particular project needs. An example schedule generated from ChatGPT can be seen in Figure 3. However, it is important to note that the schedule generated by ChatGPT may not take into account all the specific constraints, risks, and requirements of the project. Prieto et al. [37] study found that ChatGPT performance was promising for project scheduling. Still, significant flaws limit its application in real projects, indicating the potential for specialized tools to benefit the automation of repetitive and time-consuming tasks. Additionally, it may not be as accurate as a schedule created by a construction expert with experience working on similar projects. Therefore, consulting with construction experts and using specialized software to create a detailed schedule is always best. Furthermore, it is essential to validate the information generated by ChatGPT and adjust it to the specific project needs. It is also worth mentioning that ChatGPT can also be used to support construction experts by providing answers to some specific questions they may have during the construction process. Future research can look into including this powerful tool for the BIM and NLP-integrated automated CSM.

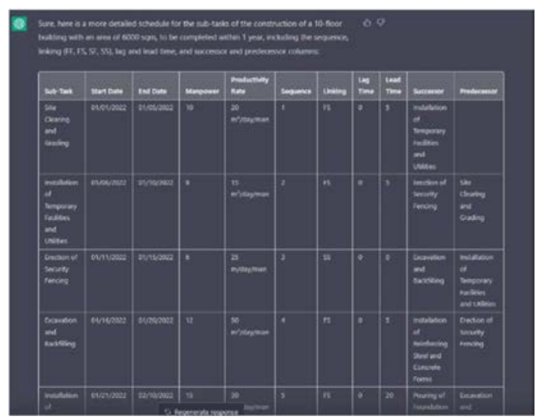

Figure 3. A sample schedule generated from ChatGPT

4 Conclusion

This study reviews the academic literature on BIM and NLP-based automated construction schedule management. It identifies state-of-the-art techniques and their limitations and challenges in widespread adoption in the construction industry. In conclusion, BIM and NLP in CSM have demonstrated significant promise for automating the scheduling process and enhancing project efficiency. However, the integration of these two technologies for CSM is less studied. Previous studies have developed and used model- and learning-based automated scheduling techniques. However, the flexibility of storing construction information, the reliance on manually created work templates, and the lack of extensive validation on actual construction projects continue to be problems for better solutions. Integrating BIM and NLP is expected to improve the efficiency and accuracy of construction schedule management through the automatic generation of dynamic work templates and the automation of knowledge learning from existing records. This integration aims to minimize the time and effort involved in schedule preparation and update and increase the precision and realism of the construction schedule. Future work will focus on multi-source data extraction and integration to fulfill automated CSM knowledge and information requirements. Research in this direction may also look into integrating large language models such as ChatGPT for automated CSM.

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